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Multi-agent Simulation Models in Agriculture: A Review of Their Construction and Uses

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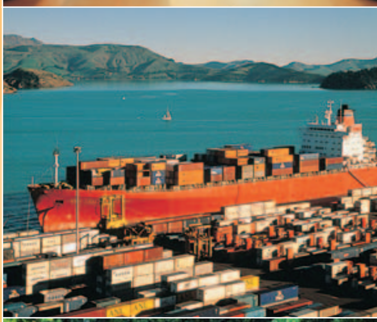

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Acknowledgements

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Executive Summary

This report lays the groundwork for modelling that forms part of the Rural Futures FRST research programme in New Zealand. The programme is a five-year FRST funded collaboration led by AgResearch. The Rural Futures programme includes the creation of an industry-level multi-agent simulation (MAS) model of New Zealand's pastoral industries. This model will describe the strategic decisions and behaviours of individual farmers in response to changes in their operating environment, and link to the production, economic and environmental impacts of their management. The MAS will need to represent the heterogeneity that exists in farmers, their systems, their responses to interventions and environmental changes, and the resultant consequences for the industry. The MAS will provide an objective tool to assist strategy and policy setters to learn about the behaviour of this complex socio-economic/biophysical system before they intervene.

A recent focus of research is complex systems whose properties cannot be modelled analytically. The theory is that emergent properties result from micro-level behaviour, from the interaction of simple agents. The interest has developed from work in physical sciences on systems behaviour, which has demonstrated the existence and importance of such systems. Systems are reduced to a few key relationships, and then the behaviour of the system under different conditions is explored by generating scenarios on computers.

One consideration is the modelling of resources. For simulating water, labour and capital, models have been developed ranging from the simple to the complex. The complexity of the modelling is generally linked to the importance of the resource; more important resources receive more attention and more complex treatment in a model. In the present research, a key task will be to identify those elements that would benefit from complex specification, so as not to overbuild the model.

A key part of MAS models is the agent. Agents in agricultural models can represent individual behaviour, making decisions and adapting to new information and experiences. MAS models can also simulate heterogeneity and interdependencies that occur among agents and their environment. This heterogeneity incorporates risk preferences and other personality traits of agents. Agent behaviour can also be described as optimising, essentially relying on an economic view of rationality, or heuristic, which relies more on descriptive or qualitative information about behaviour.

When the model as a whole is considered, a number of issues become important. There are technical issues, such as the time-step in the model (how often a decision or action is made) and the method for simulating markets. Wider considerations include testing for the validity of the model – that it is simulating the appropriate things – and the verification of the model – that its simulations are accurate.

Success can be assessed along several dimensions. A key concern for this FRST programme is that the model be usable and useful for end-users. Given the mixed success of MAS models with uptake by end-users, decisions will need to be taken about user involvement and influence on model development. Participatory modelling is one approach that provides a useful tool for involving stakeholders and end-users at each stage of the model development process.

This review is intended to provide some guidance on the essential components of a model, methods for modelling each component, and processes for assembling an appropriate and usable model. With a successful model, the programme should be able to assess the macro-level emergent properties of New Zealand agriculture by simulating micro-level behaviour of farms and farmers.

Chapter 1
Introduction

In recent years, there has been increasing interest in economics in systems that are not in equilibrium or that, indeed, have no apparent equilibrium state. This interest has developed from work in physical sciences on systems behaviour, which has demonstrated the existence and importance of such systems. Often, these are complex systems with multiple feedback loops and independent and interdependent actors. They are also adaptive, dynamically changing to respond to environmental conditions. Mathematical and computational tools have been developed to analyse these systems. An important tool is *simulation*, by which a system is reduced to a few key relationships, and then the behaviour of the system under different conditions is explored by generating scenarios on computers.

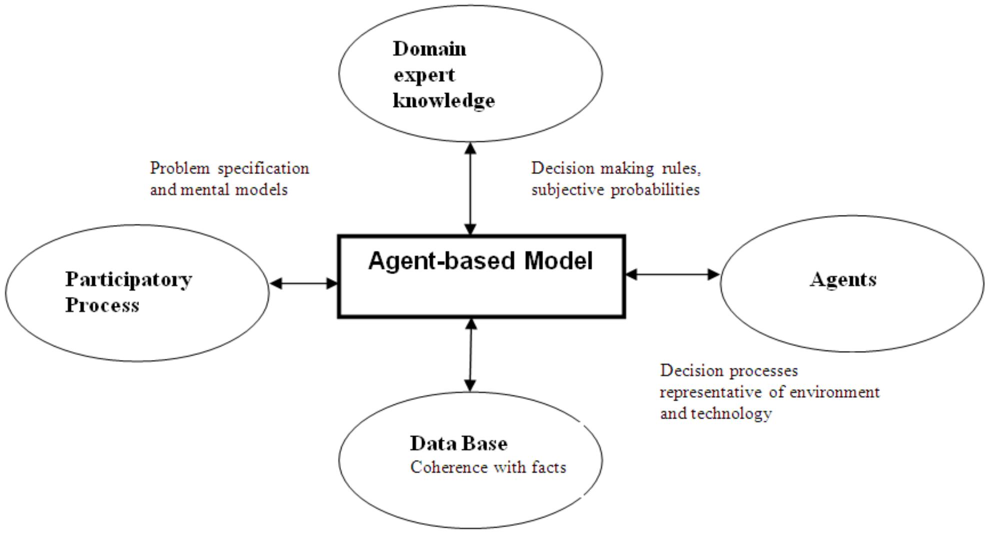
These simulations are often agent-based models, in which individual agents are the basic unit of modelling for a complex system. The agents represent individuals' behaviours in response to their local environment. They interact with each other and their environment, and make decisions and changes as a result of this interaction. The whole system behaviour depends on the aggregate behaviour of individual agents (Matthews, Gilbert, Roach, J.G., & Gotts, 2007). Agent-based modelling is a bottom-up method of modelling complex systems. Core premises for agent-based models are that agents are the decision-making components in complex adaptive systems. These systems are created by the independence of the agents' cognitive behaviour, decision behaviour, and heterogeneity. Importantly, the behaviour of a complex adaptive system can be characterised by emergent properties, results that cannot be found analytically but rather are the result of the system's behaviour (Matthews et al., 2007; North & Macal, 2007; Tesfatsion, 2006).

Agriculture appears to be such a system. Whether from the farm perspective or the industry perspective, agriculture can be considered a complex adaptive system of multiple actors and nested levels responding to changes in the environment that its activities help produce. Researchers have begun to use simulation models with multiple, interacting agents to describe agriculture, and then use these models to examine the impacts of exogenous changes to agriculture. It has become a common method of modelling complex real world systems in the land-based sector. These systems range from cattleherders in North Cameroon (Rouchier, Bousquet, Requier-Desjardins, & Antona, 2001), to deforestation/afforestation in Indiana (Hoffmann, Kelley, & Evans, 2002), to farming in the German region of Hohenlohe (Balmann, Happe, Kellermann, & Kleingarn, 2002).

This report reviews the literature on these models. It lays the groundwork for modelling to be undertaken as part of the Rural Futures FRST research programme in New Zealand, which is a five-year FRST funded collaboration including AgResearch, Lincoln University, Otago University, and The Agribusiness Group. The Rural Futures programme includes the creation of an industry-level multi-agent simulation (MAS) model of New Zealand's pastoral industries. This model will describe the strategic decisions and behaviours of individual farmers in response to changes in their operating environment, and link to the production, economic and environmental impacts of their management. The MAS will need to represent the heterogeneity that exists in farmers, their systems, their responses to interventions and environmental changes, and the resultant consequences for the industry. The MAS will provide an objective tool to assist strategy and policy setters to learn about the behaviour of this complex socio-economic/biophysical system before they intervene.

Figure 1.1 shows the process of agent-based model construction and iteration (feedback) between considered core model components. Underlying this simplistic representation is a complex mathematical and model logic, with associated coding and algorithms designed to represent phenomena associated with agent interaction and bottom up emergent property outputs.

Figure 1.1: Spatial data representation of a multi-agent system (adapted from Pahl-Wostl, 2002)



Berger (2001, p. 246) defines MAS as 'computer systems composed of autonomous entities or agents which have only limited knowledge and information processing capacities ... typically they are larger entities with some sort of persistent control'. Many MAS models have been developed for understanding and modelling land based systems, such as AgriPoliS (Happe, Kellermann, & Balmann, 2006), MPMAS (Berger, Schreinemachers, & Arnold, 2007) and SYPRIA (Manson, 2005). The structures of these models are varied, but generally fit an actor–institution–environment conceptual model as in SYPRIA (Manson, 2005). In such a modelling system, key actors are farmers or households and are agents in the model. Institutions are other agent types, such as regional councils, the market, and RMA, who guide agents' decision-making. The environment defines the actors' bio-geophysical context, including elements such as climate and soil. Three major processes are sequentially executed during each time-step of the simulation. First, institutions change variables related to actors' decision-making; this is a policy change. Secondly, the environment changes according to endogenous ecological rules and the effects of actor decision-making during the previous time-step. Thirdly, each actor in the region makes land-use decisions. Contributing to these decisions is information transfer among the agents, which affects opinion formation, the rates of adoption of new technology, and adaption to new policy and environmental changes.

A review of the recent literature on agent-based models (Axelrod, 2006; Axelrod and Tesfatsion, 2006; Berger, 2001; Bruun, 2004; Buchanan, 2005; Buxton et al., 2006; Gilbert and Terna, 2000; Matthews et al., 2007; Midgley et al., 2007; North and Macal, 2007; Parker et al., 2003; Tesfatsion, 2006) identified a number of benefits and strengths of MAS.

- It is a practical methodology to address agent interaction that is reliant on both past experience and agent adaptation.

- It can address and facilitate inter-disciplinary collaboration, and can incorporate data from multiple disciplines.

- MAS models are able to interpret reactive, goal-directed and decision-making entities as they react to their environment.

- Building a MAS follows bottom-up principles (see also Barnaud, Bousquet, & Trebuil, 2008), producing the aggregated, macro-level performance of a modelled system from micro-level behaviour.

- MAS models enable a 'third way' of doing science (in addition to deductive and inductive[1]) where empirical data originates from emergent properties derived from defined rules developed from historical real-world observations.

- These models allow representation of the temporal and spatial complexity in land-based systems characterised by interdependencies, heterogeneity and nested hierarchies.

- Upward and downward linkages in modelled systems are captured, and the emergent structures accommodate exogenous shocks and system critical mass and perturbations.

North and Macal (2007) see the MAS paradigm as useful in business decision-making and innovation, encompassing operational, tactical and strategic level roles. Modelling and simulation are seen as components of a larger analytical framework compiled to understand and ultimately control business processes and organisations. In effect, they see a role for agent-based model simulation in using participatory simulation with a goal in identifying agent behaviours at the micro-level, ultimately resulting in macro-level outcomes. With regard to supply chain modelling, agents are considered the 'decision-making members', with North and Macal (2007) using both a theoretical network beer game simulation and a practical deregulated electricity generation and supply model as examples of use of agent-based model simulation.

A number of the strengths of MAS models are defined in opposition to equation-based modelling. Equation-based models are most naturally applied to systems that can be modelled centrally, and in which the dynamics are dominated by physical laws rather than information processing. In contrast, MAS models are most appropriate for systems characterised by a high degree of localisation and distribution and dominated by discrete decisions. This has been evaluated previously by Van Dyke Parunak et al. (1998) where similarities and differences between the two modelling techniques were assessed[2]. They stated that equation-based models and MAS models differ in the fundamental relationships amongst entities being modelled, and the focus levels of attention. In particular, equation-based models use sets of equations to express relationships among observables, while MAS models use behaviour modelling through which individuals interact. Van Dyke Parunak et al. (1998) demonstrate that equation-based models make extensive use of system level observables whereas agent-based models define agent behaviours at the individual level.

A key question is the extent of the complexity to include in a specific model. Two metaphors were developed by Casti (1997) which were used by Parker et al. (2003) in their review of

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[1] Inductive approach being empirical data pattern discovery, and deductive approach using hypotheses and observation in prediction true/false derivation (see Matthews et al., 2007).

[2] Whilst Van Dyke Parunak and colleagues did note the issues of both competition and criteria for selection of either model technique in their critique, subsequent advances in the fields of both system dynamics and agent-based models appear to have illustrated a collaborative and 'added value' relationship between the modelling methodologies (e.g. refer North & Macal, 2007; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003).

MAS models of changing land-use or land-cover use. The first metaphor is that of a photographic portrait and the second is that of a Picasso portrait. In the photographic portrait metaphor Casti describes models in which all of the variables present in real life are modelled as faithfully as possible in a spatial MAS model. This spatial modelling method will be described in more detail in Chapter 2. In the metaphor of the Picasso portrait, Casti describes models in which the attempt is to identify key features of a problem and highlight those in an attempt to emphasise the fundamentals of a particular problem. Parker et al. (2003) terms the analogy of the photographic portrait the descriptive approach, whereby models try to recreate the subject as closely as possible in an effort to maximise empirical and predictive validity. The Picasso analogy is termed the explanatory approach, in which the goal for the model is to explore theory and generate new hypotheses. This differentiation of the two approaches is similar to the later discrimination of the abstract and experimental model from the empirical model by Berger et al. (2006).

Models are not necessarily of one type or the other. Rather, they vary along a dimension in which one end is anchored by a photographic/descriptive ideal, and the other end is anchored by a Picasso/explanatory ideal. Nor is it necessarily the case that every variable in a given model should be treated in the same way. Part of the process of model building is identifying how elements of the model should be treated, given the goals of the research. For some elements, precisely describing their attributes may be vital for the research. For example, it may be important to be precise about the greenhouse gas emissions from different animals and production systems in a land-use model. In the same model, it may be possible to treat other variables less precisely. Profitability of a land use may, for instance, be considered in a general way, rather than calculated exactly with a production budget or model farm accounts.

MAS models have found application in areas other than agriculture. They have been used to model an aero-engine value chain experimentally in order to understand the underlying dynamic behaviour, which results from collective behaviour and interactions, and to illustrate the potential use of the modelling to support strategic decision-making (Buxton, Farr, & MacCarthy, 2006). Actors in the value chain are represented as 'agents' with individual processes, logic, risk attributes and market sector responses. The researchers noted, however, that the model experiments were purely illustrative and hypothetical (Buxton et al., 2006). At a more applied industry level, Keenan and Paich (2004) describe a General Motors' North American automobile market model based on both a structured enterprise model (system dynamic) and a more complex consumer choice model (agent-based). In interpreting both qualitative and quantitative insights, Keenan and Paich (2004) derived policy scenario outcomes, but also highlighted the role of the agent-based model in the research. Further examples of industry level applications of agent-based models within multi-national businesses are provided by Buchanan (2005), where agent-based models assist in 'seeing around corners' and 'penetrating the confusion' of business strategic scenario complexity and understanding.

Decision behaviours in agent-based models are particularly important in the emerging field of agent-based computational economics (ACE; Tesfatsion, 2006). The observation that an economy is a large composite system has led to it being analysed as a complex, dynamic, and adaptive system. Such systems have a large number of interacting units or agents, whose interactions result in emergent properties (Bruun, 2004; Tesfatsion, 2006). As an illustration of ACE, Tesfatsion (2006) uses the perturbation and progression of the Walrasian equilibrium model[3]. The model solution is actively driven by agents, who incorporate strategic rivalry,

[3] A precisely formulated set of conditions under which feasible allocations of goods and services can be price-supported in an economic system or organised on the basis of decentralised markets with private ownership of productive resources (Tesfatsion, 2006).

power, behavioural uncertainty, learning, and information procurement and diffusion in a complex computational environment. The development of an ACE model encapsulates both constructive mathematical programming, and economic and social science theory.

The review presented in this report focuses on the core components for the development of a MAS model for New Zealand's pastoral industries. This introductory chapter has presented the rationale for MAS models, described some of their uses and strengths, and highlighted some areas where they have been used. The second chapter describes options for modelling land and other resources that are important variables for the development of a MAS model for New Zealand. The third chapter focuses on the agents and the heterogeneity they represent. In this context, the key drivers of the decision-making process such as information transfer and opinion formation are outlined and also risk preferences and other personality traits of the agents are presented. The fourth chapter considers some issues in bringing the different components of the model together. The fifth chapter describes usability and end-user requirements of the MAS model as a challenge for the successful development and implementation of a model. The final chapter summarises the findings to support a model of agriculture in New Zealand.

Chapter 2
Modelling Resources

There are a number of resources that could be included in a model of farming in New Zealand. Among the most important of these are land, water, labour and capital. Many agent-based models have been developed that together present a variety of approaches for modelling these variables. In general, each of the resources can be addressed using techniques ranging from the simple to the complex. For example, a resource could be included in a more general variable representing total resources or productivity; represented with a randomly generated value for the variable; assigned values based on empirical data; or indeed ignored in a model as practically unimportant. A more complex representation of a resource could be included with a dynamic sub-model. For example, water in a model of farming could be predicted with a complete hydrological system. An appraisal of some applications of agent-based models within the natural resource and land-use, business and economics fields of study is presented below.

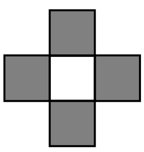
2.1 Land

In a model of farming, the question of land is central. This discussion of resources thus starts with how land was represented in various models, and how land was linked to other parts of the models.

Perhaps the simplest method for modelling land was used in a model of cattleherders in North Cameroon (Rouchier et al., 2001). In their model, the authors were interested in replicating the system by which cattleherders in North Cameroon rent access to grazing from farmers during the dry season. To model this system the authors randomly assigned a value (between certain parameters) for the number of villages in a given model run, a value for the number of farmers in each village and a value for the number of fields for each farmer. In this way their model did not attempt to represent land spatially. However, this simple method for modelling land worked well with their model because it paralleled the way in which their cattleherder agents went about renting land: first they choose which village headsman to approach for access rights. Once the access rights for the village had been gained the herdsmen chose which farmer they wanted to approach for specific land/grazing rights. Thus, it was not of interest to model different geographies, soil types, costs of transport from the farmstead to a field, nearby neighbours, or any other spatially oriented variables.

In what is almost a diametrically opposed starting point regarding the way in which land can be modelled, Balmann (1997) created a model of farming that was almost purely spatial and represented land using a cellular automata (CA) model. CA models use a grid/square structure in which each square is connected to its four neighbours (See Figure 2.1).

Figure 2.1: Visualisation of a Cellular Automata Model



Using CA to model land requires a more complex computer programme than the non-spatial model used by Rouchier et al. (2001). However, its chief advantage is that once the CA structure is programmed, any number of different spatial variables can easily be assigned to each cell. In addition, because each cell has a specific location, CA models can be created using GIS data or other regional, spatial data. For example, in his model, Balmann (1997) used the CA structure to assign cells different values for whether the cell is the farmstead (and thus owned) or rental property, the distance the cell is from the farmstead, the current land-use, etc. In addition to the CA structure, the model included farms which had values for variables such as labour, employment of additional personnel, casual labour, access to capital, assets, age, total income, total rental costs, and total transportation costs from all the farm cells.

Recent work in modelling systems in the land-based sector has developed a number of models that explicitly combine the MAS approach with the spatial modelling CA approach that Balmann (1997) used. By combining both a CA sub-model and a MAS sub-model, variables can be divided into spatial variables that are assigned to cells in a CA component and personality/behavioural/decision-making variables that are assigned to agents in the MAS portion of the model. For example, Torrens (2001) used a CA/MAS model to create a simulation of urban communities. In the model, each CA cell represented a piece of property in a neighbourhood or city. Each cell had values for the value of property, housing type, lot size, housing tenure, density, land use, number of bedrooms, rental value, and a discounting function. In the MAS portion of their model, they used agents to represent homebuyers and sellers. Their MAS agents had the following attributes: income, age, children, household size, ethnicity, inertia, residency, segregation preference, lifecycle stage, tenure preference, housing preference, housing budget, willingness to leave submarket, socioeconomic preference, and agent type. Their model also provides a useful illustration of the number and diversity of factors that can be taken into account in these models, from prices for a given piece of property to personal traits such as the housing preference of a given agent. In addition, their model also clearly shows how variables can be divided and tied to either the spatial CA sub-model or the MAS sub-model.

Another interesting model is Berger's (2001) model of agriculture in Chile. In his model, he assigned values to each of the cells in the CA matrix for soil quality, water supply, land-cover/land-use, ownership, internal transport costs (from the farmstead), marginal productivity or return to land. Although the exact variables assigned to agents are not listed, by implication they included at least the amount of rented land and water rights, calculations for the highest utility for each use for each parcel of land, a variety of behavioural constraints to create heterogeneous financial and technical behaviour, differing rates of information adoption, and the ability to 'leave' farming if income drops below a certain level.

The work by Berger and others (Berger, 2001; Berger et al., 2006) also demonstrates the use of CA/MAS modelling for policy assessment. The model was focused on land use in developing agro-ecological zones, and has been applied to the biophysical and socio-economic constraints evident in Uganda and Chile. The models in this context represent multi-layered spatial data, organisation into sub-models, and direct agent/environment interaction. In assessing the feasibility of and constraints to increasing agricultural productivity in a district of Uganda, Berger et al. (2006) created a bio-economic model using mathematical programming for agent interaction and decision-making, neural networks as yield estimators, and nutrient balances for ecological sustainability. The aspatial, non-connected MAS consisted of independent farm models for comparative-static analysis. Simulation scenarios examined farm household tradeoffs, and results were analysed to identify binding constraints for profitability and sustainability. Additional research assessed the impacts of technology adoption and policy intervention within an agricultural study region of Chile (Berger, 2002, Berger et al., 2006). The work provides an example of simulation scenario analysis, where both interactions and heterogeneity of policy response are captured by extensions of a static non-connected MAS. The model included agent and land parcel information and interaction exchange, agent decision-making specification, and agent sequencing. The modelling examined policies aimed at promoting innovation diffusion, and showed that well-targeted extension programmes were cost-effective via client innovation and linkage within their environmental and socio-economic zones (Berger et al., 2006). Given the relatively high degree of policy complexity, with interventions targeted at constraining land and resource degradation in developing countries, the MAS approach was considered a better approach than more conventional bio-economic analyses (Berger et al., 2006).

Manson (2000) developed a very detailed model of reforestation in the Yucatan peninsula of Mexico. He was interested in replicating a theoretical model in which the actors, environment and institutions were all mutually interdependent. To replicate this theoretical model required a very detailed CA/MAS model. In the CA portion, each cell had values for a wide range of variables, including land use; land cover; soil fertility as a function of cover, past soil fertility, and duration of present land use; environmental attributes of hydrology, soil type, slope, and aspect; suitability of three production activities (agriculture, forestry, and nontimber forest products); and distance to market and transportation infrastructure. To model both the agents and institutions described in the theoretical model, Manson developed two types of agents for his CA/MAS model: smallholder and institution agents. The institution agents were used to communicate information to the smallholder agents about land tenure; about different markets, such as crop and fuel prices; and about government subsidies. The smallholder agents acted as the agents in the theoretical model and it was their actions that directly determined the land use/cover for each cell in the model.

Balmann, et al. (2002) created a model of farming in the German region of Hohenhole to investigate changes in European Union farming laws and subsidies. This model is similar to the Manson (2000) model described above. The CA cells tracked values such as the distance from the farmstead, suitability of the area for grassland or arable farming, and the current use of the land – dairy, cattle, suckler cows, sugar beets. The farms in the model acted as the agents and made choices about whether to take on more loans, rent or buy land, hire additional labour, or use labour and capital for off-farm employment (that is, leave farming).

Balmann was also involved in the development of the AgriPoliS simulation model. This spatial and dynamic MAS simulated endogenous structural change in agriculture, more specifically EU agricultural structural change and the policy impacts therein (Happe, Balmann, & Kellermann, 2004). The model mapped the key components of regional agricultural structures in a complex, evolving system. It included heterogeneous farm enterprises and households, spatial parameters, and market and production factors, all embedded in a techno-political environment. Farm agents (farm manager and farm household decision-makers) were the key entities (together with market agents), interacting with their ‘environment’ and engaged in land rent and disposal, plus associated agricultural production and marketing activities. Parameters of interest for end-users were macroeconomic framework conditions, the policy environment, technological change and on-farm socio-economic characteristics. A key outcome for the research was analysis of agricultural policy and assessment of interrelationships amongst land rents, technical change, product pricing, investments, productivity and policy intervention (Happe et al., 2004). Data outputs were on both individual farm and aggregate data level (Happe et al., 2004).

The objective of the FEARLUS project (Polhill, Gotts, & Law, 2002) has been the application of MAS techniques to questions of significant land-use change, such as government intervention, market driven change, and environmental change. The spatially based land-use model is abstract, but designed to clarify aspects of land-use change in Scotland based on dimensional-grid cells of land parcels. Polhill et al. (2002) used land manager 'agents' (conceivably farm family units or organisations) acting within both social and physical neighbourhoods. Simple heuristic models were utilised, where imitative strategies were employed with regard to historical land-use, climate, economy, neighbouring cells, biophysical properties of land, and agent cognitive preference. The FEARLUS model outputs were aimed at policy makers facing land-use decisions. The model was also a possible educational tool, offering the possibility of exploring land-use options by modelling scenarios in a multi-dimensional framework (Polhill et al., 2002).

2.2 Water

Another important resource in agriculture is water. Berger's (2001) representation of water is perhaps the most comprehensive of the models discussed. The model of farming in Chile used an explicit hydrological model including variables for locally available freshwater supplies, irrigation and return flows and used equations and parameters for these values derived from the Chilean Department of Public Works. In addition, the course of water was mapped through the CA structure, thus those that took water out for irrigation 'upstream' left less water for those downstream. Finally, this hydrological model was tied into the model for renting water rights, which further contributed to the hydrological model by establishing precedence in removing water from the system.

Other models have taken a less complex approach to modelling water. For example, Rouchier, et al. (2001) modelled water simply as a value for the number of good or poor watering sites each village had access to, which they could then rent to the herdsmen. A number of the models described above have no explicit model for water. Instead, water availability was inferred from other variables that are perhaps more proximal to farming outcomes, such as the productivity of a given piece of land, or its suitability for a certain type of land-use (Balmann, 1997; Balmann et al., 2002). It is also possible to model water explicitly without a hydrological model; Manson (2000) used a simple model that assigned values for hydrology and precipitation for each CA cell.

In the end, the modelling of water in a system only needs to be as complex as required for the issue at hand. In modelling farming behaviour in a dry region such as Chile, a more specific model for water will probably lead to better replication of empirical data and patterns. On the other hand, it is just as plausible that choosing a simpler approach, especially for regions in which water challenges might not be a primary issue in farming, might be preferable.

2.3 Labour

Labour is another resource included as a variable in some MAS models. In some of the models detailed rules were set, e.g., Balmann (1997) and Balmann et al. (2002). In these models the amount of labour at each turn was based on multiple factors. First, each farm started with an initial amount of labour available. This amount of labour could then range higher as more labour was hired, or range lower as the initial labour was put to use in off-farm employment. Finally, off-farm employment could consume the entire initial on-farm labour, thus allowing the agents 'leave' farming altogether. In addition, the models allowed for labour units to be divisible, e.g., a farmer spends some of his time in off-farm employment. The costs of labour and increases in productivity were then used in the linear model by which the farm agents made their allocation decisions.

As was the case with water modelling, some models did not directly take into account access to labour resources. For example, Rouchier, et al. (2001) had no market for additional labour and instead assumed that each herdsman agent would be able to provide enough labour to keep a herd of infinite size. Herd size was still limited by available water and land access however, so the practical outcome was simply that herds were limited to no more than a couple of hundred animals for even the largest herds. Thus, if the type of farming or the region being modelled has access to a labour market, and labour is one of the constraints on production, then a model that incorporates this may lead to more realistic outcomes.

2.4 Modelling capital

The treatment of capital also varied across the models. In some cases capital is a detailed and important part of the model and in other cases capital is not included. The models in Balmann (1997) and Balmann et al. (2002) again provide one of the more detailed and inclusive models with regard to capital. In their models, agents have access to liquid equity capital with its associated opportunity costs, short term loans and long term loans. The maximum additional long term credit a farmer has access to in the model is defined in equation 1:

$$G \leq (L - E)\,(1 - v) / v \qquad (1)$$

In this equation a minimum reserve is subtracted from liquidity and the sum must be higher than the share of the acquisition costs that is financed by the equity capital. Their decision making model then also accounts for repayment of debts, assets, income, and long-term interest expenses, to fully model capital.

In other, less financially oriented models, capital is not accounted for at all. Again, Rouchier, et al.’s (2001) simple model of herdsmen did not require the introduction of any form of capital market to successfully model the behaviour in which they were interested.

2.5 Markets for resources

Another issue to consider regarding resources is how allocation changes during model simulations. Two interrelated issues are the method for allocating resources, such as through markets, and the method for arriving at a market solution for produced commodities. This section considers the former, while the latter is covered in Chapter 4. Six mechanisms for allocation are apparent in the literature, including four methods reviewed by Lebaron (2006) and two others that also appear in other models.

The first mechanism is simply to assign productive resource to agents for each simulation, and leave the allocation unchanged. Resources are thus inseparable (not *alienable*, to use a legal term) from the agents who use them. This approach simplifies the modelling. However, it also reduces the amount of information that can be generated by a model, such as the price of land parcels.

A second mechanism is to establish a market for a specific resource, including a supply and demand. A price adjustment mechanism can then be created that allows the market to adjust over time. With this type of market, agents put in orders for buying and selling and these orders are then summed. The price is increased if there is excess demand and decreased if there is excess supply. This description of a market is similar to a cobweb model (Nicholson, 1992), in which a market goes through several iterations to approach an equilibrium. The magnitude of the increase or decrease varies with the magnitude of the imbalance and the strength of the constant assigned in the equation. In this way, it is possible for markets to spend a great deal of time away from a market clearing value. Lebaron (2006) argues that it is both an advantage and a disadvantage that the market model is not in equilibrium. It is an advantage in that a market in disequilibrium might be a more accurate portrayal of the market in reality. The disadvantage of this market mechanism is that, depending on the value assigned to the change coefficient, the market might spend a good deal of time far from market clearing prices. In addition, if this method is chosen for a resource market, a decision must be made with regard to the treatment of excess demand. This demand can be filled from some inventory, which can itself be modelled, or a supplemental rationing system can limit demand filled to the supply produced.

A third mechanism available to model resource markets is to calculate a temporary market clearing price based on current supply and demand. Lebaron (2006) suggests that the benefit of this type of model is that the prices by design always clear the market, thus no issues arise involving a market maker, inventories or rationing. However, this type of market mechanism may enforce an equilibrium when one does not exist in the actual resource market in question. In addition, this method of clearing the market can involve a great deal of computation or, in an effort to limit the computational requirements, it can lead to an oversimplification of agents' demands. However, this mechanism most likely captures the variety of auction based methods that the farm models discussed have handled their markets. Brock and Hommes (1998) created an asset pricing model using this mechanism. In their model, they solved for the price of their assets with the following equation:

$$Rp_t = E_{ht}(p_{t+1} + y_{t+1}) - \alpha\sigma^2 z_{st} \qquad (2)$$

In this equation Rp_t is the price in the present turn, which equals the expectation (E_{ht}) of an investor of type h at time t of the sum of the future price (p_{t+1}) and the future increase (y_{t+1}), from which is then subtracted the product of risk (α), variance (σ^2), and the supply of shares per person (z_{st}). If there is no external supply of shares, the equation reduces to

$$Rp_t = \Sigma n_{ht} E_{ht}(p_{t+1} + y_{t+1}). \qquad (3)$$

The price is thus given by the sum of expectations over all the types of investors at a given time.

A fourth mechanism for allocating resources dynamically is to borrow the idea of order books from real world markets and have the agents' orders filled using some well defined procedure. From a microstructure perspective, this mechanism has the advantage of being the most similar to the way in which some markets operate in reality, for example, financial markets. A drawback to this mechanism is that it requires the modeller to include a great deal of institutional details into the market structure and into the agents' learning model. An example of this market mechanism can be found in Farmer, Patelli, and Zovko (2005). They created a model that used the continuous double auction method, the same method widely used in modern financial markets. Agents in the model could submit orders to buy and/or sell at any point in time. In addition, both market and limit orders could be placed by agents. A market order was defined as a buy or sell order that crossed the opposite best price and a limit order was defined as a buy or sell order that did not cross the opposite best price. Just as in real financial markets, limit orders were queued and allowed to accumulate until market orders were placed, which then removed them from the queue. The lowest selling price offered at any point became the best ask price (a_t), the highest buying price was the best bid price (b_t), and the bid-ask spread was defined as $s_t = a_t – b_t$, the gap between the two.

A fifth mechanism, used by Lebaron (2006), is to allow resource transfer only through direct contact between agents. This mechanism requires some sort of spatiality to the model, such as a CA structure, to determine which agents are 'neighbours' and then allow trading only between neighbours. For some resources, this may be an accurate model for a market. For example, in models that allow the purchase or rental of water rights (e.g., Berger, 2001) the most accurate model could be one in which only neighbours are allowed to trade water rights. An example of this market mechanism is the way in which Rouchier, et al. (2001) dealt with their market for herdsmen renting land. In the model, each herdsman was allowed only a certain number of times to approach headsmen and farmers each turn and transactions were carried out directly between the herdsman agent and the village headsman agent or the herdsman agent and the farmer agent.

A sixth mechanism is an auction, in which agents directly compete for specific resources. A number of examples of this mechanism appear in the farm models reviewed. For example, both Balmann (1997) and Balmann et al. (2002) used auction models for their markets of land purchase and rental. Specifically, each farm sequentially bid on plots of nearby land. A farm's highest bid for renting ($R_{y,x}$) was, 'the difference between the additional gross margin Δ and the transport costs $TC_{y,x}$ (which depend on the Euclidean distance between the farm's location and plot (y, z))' (p. 98):

$$R_{y,x} = \Delta - TC_{y,x} \qquad (4)$$

Bidding on plots continued until bids dropped below zero. Berger (2001) also used an auction-based market for his model of Chilean farmers. If a farmer's shadow price for a given plot of land was below the average for that sector they attempted to rent out the land and associated water rights. The land and water rights were then transferred to the farmer with the highest shadow price for that specific parcel.

The dynamic allocation mechanisms described are generally guided by prices, depending on the values and price expectations of buyers and sellers. Prior research on the agricultural sector has established the importance of networks and relationship to agribusinesses (Saunders, Kaye-Blake, Hayes, & Shadbolt, 2007). Rouchier, et al. (2001) designed the only model reviewed in this report to use relationships as a factor in the agents' decision making. In their model of herdsmen in North Cameroon, they designed one variation of their model in which the agents pursued a strategy attempting to maximise their profits. In a second design of their model, agents pursued a strategy in which they tried to maximise their relationships with the various farmers whose land they were renting. They pursued this strategy by preferentially asking the farmer with which they had most often been able to rent grazing land from in the proceeding rounds. In this way the authors were able to set up an alternate model for the herdsmen agents' decisions for which farmer was approached first. This approach then allowed the authors to compare the outcomes for a model in which herdsmen rented based on relationships, with a model in which agents simply went to the farmer with the cheapest land to rent. Creating a model that tracked the rent versus refusal decisions between the herdsmen and the farmers also allowed the authors to examine and define 'relationships' in their model. For example, for a given simulation run, if a herdsman and a farmer successfully reached an agreement on more than half of the rounds then they were considered to have a 'relationship'.

2.6 Summary

Numerous agent-based models have been created that together cover a variety of approaches for modelling resources such as land, water, labour and capital. These are the most important variables for the development of a MAS model for New Zealand's pastoral industries.

With regard to modelling land there are two general approaches, a non-spatial and a spatial approach. The models that represented land spatially used a Cellular Automata (CA) model. The specific characteristic of a CA is that after the structure is set other variables can be assigned to each cell of the model. There is also a combination possible that incorporates a CA sub-model and a MAS sub-model. The variables can then be divided into spatial variables and additional variables can be assigned to the MAS part of the model such as personality/behavioural/decision variables. Predominantly, the CA/MAS approach was used in the reviewed literature.

With regard to simulating water, labour and capital, models have been developed ranging from the simple to the complex. For example, the development of a complex approach for modelling water might be useful where water demands are a main issue in the farming sector. A similar decision has to be taken when modelling labour is questioned. If labour has a high impact on farmer's decision making then a model that incorporates labour access may be a better fit to the problems modelled. Much the same decision has to be taken when capital should be a variable in the model. If it is a financially orientated approach, the model agents may have access to liquid equity capital but there are several models in which capital is not incorporated.

Several potential methods for adding dynamism to the allocation of resources were discussed. The complexity of the methods varied. Simple exchange can be modelled with supply and demand equations or schedules for the resources. More complex models may include expectation about future earnings from the resources, or information about the traders, such as the location of traders or the history of the relationships of the agents.

Many prior methods have been used for modelling resources. Importantly, the complexity varies with the focus of the research. The most complex components of prior MAS models are those focused on the most important element of the research, whether this is local hydrology or the role of interpersonal relationships. Other elements deemed less important are simplified. In the present research, a key task will be to identify those elements that would benefit from complex specification, so as not to overbuild the model.

Chapter 3
Agents, Information, and Heterogeneity

Agents are key for MAS models. They represent individual behaviour, interact with each other and their environment, and make decisions and changes as a result of this interaction. Information transfer between agents occurs through communication networks and is an important element of the decision making process of agents. MAS models can also simulate heterogeneity and interdependencies that occur among agents and their environment. This heterogeneity incorporates risk preferences and other personality traits of agents. The purpose of this chapter is to review the treatments of information and heterogeneity in MAS models. In particular, the chapter considers approaches to simulating information transfer and decision making in existing MAS models designed for policy setting and strategy setting in agricultural systems. It also examines the incorporation of risk preferences and personality traits into the decision making process of the agents.

3.1 Modelling information transfer, agent learning and opinion formation

Information transfer can be important for the decision making process and therefore an important process for the development of a MAS model. Information transfer is linked to learning processes. A large number of models have been developed that include agent learning processes for different situations. Opinion formation is another process that is important for the representation of agents in a MAS model and strongly related to information transfer: opinion formation depends on collecting information. These three elements of modelling decision making are discussed below.

3.1.1 Information transfer

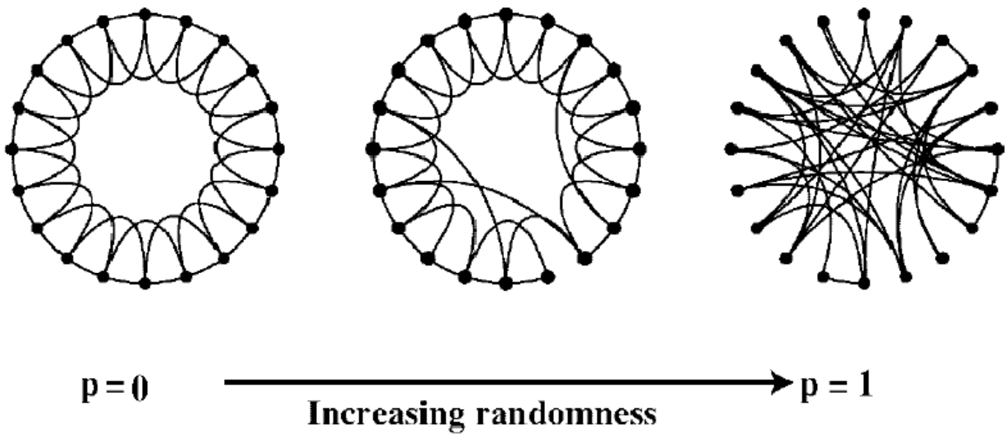
In empirical MAS models in the land-based sector, an agent may represent a farm household. Farm households combine individual knowledge and values, biophysical landscape environment, and assessment of the land management choices of neighbours to make land-use decisions (Berger et al., 2006). The interaction of farm agents through communication networks is an integral part of decision making. Communication lowers the uncertainties for agents (Berger et al., 2006), but slows down decision-making processes (e.g., adoption rate of innovations (Berger, 2001)).

In a MAS model, agents are explicit entities. Inter-agent communication can either be direct (agent-to-agent) or indirect (agent-environment-agent). It can be explicitly implemented using message passing, such as with an announcement of a new environmental policy. Using the Unified Modelling Language (UML) to draw a sequential activity diagram of major agents, including explicit information transfer, can be very helpful to clarify communication among agents (e.g. in Happe et al., 2006; Schlüter & Pahl-Wostl, 2007).

Modelling information transfer and its associated network structure replicates one of the key drivers of an agent's decision making: information sourced from other agents in a social network. Information transfer plays two key roles. It creates a basis for social comparison (Festinger, 1954) and is a source of information and opinion (Anderson, Beal, & Bohlen, 1962). The responses of individual agents and the movement of information through networks can lead to emergent properties of the system.

The underlying network structure used for information transfer between agents, otherwise called a social network, is important (Milgram, 1967; Watts & Strogatz, 1998). Social networks exhibit qualities of 'connectedness' that have properties of both highly uniform networks, e.g. lattices, in that groups of nodes are interconnected; and of highly random networks in which the distance between any two nodes is quite short (i.e. six degrees of separation, Watts, 2003) (Figure 3.1).

Figure 3.1: Connectedness of social networks (Watts, 2003)



A number of techniques exist to construct these specific classes of network, most often referred to as small world or scale free networks (Barabási & Albert, 1999; Newman, 2003; Watts & Strogatz, 1998). These models can be used to construct networks with similar qualities to those seen in real social networks. Formal validation can be difficult due to the inherent dynamic nature of real social networks (Robins, 2009). However, information transfer via a social network plays an important role in agribusiness decision making and as such deserves consideration (Saunders et al., 2007).

3.1.2 Agent learning

A large number of models are available for representing agent learning (Brenner, 2006). Types of models include:

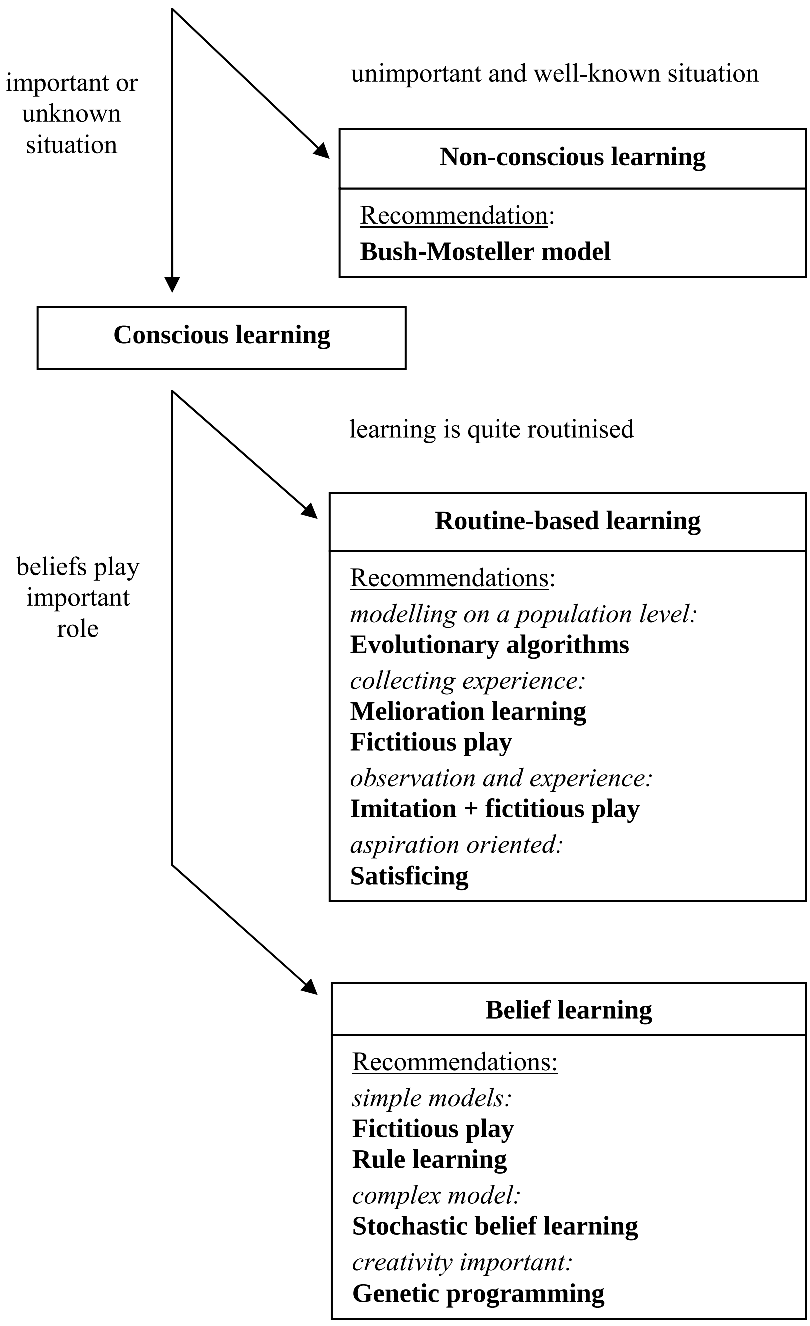
- psychology-based, such as reinforcement learning;
- probabilistically optimal, including Bayesian learning and least-square learning;
- adaptive learning, such as learning direction theory; and
- belief learning, e.g., fictitious play.

The development of these models over time can be modelled using evolutionary algorithms or neural networks. In addition, agent learning can be represented at population, sub-population and individual levels.

These models have different purposes or emphasise different aspects. A model may aim to describe real learning processes, or simulating their implications for economic processes instead of learning processes *per se*. It may also aim at leading to an outcome that corresponds to empirical observations, or at developing clever or even optimal learning models. There exist two schools of thoughts in economic learning and optimisation: one prefers learning models that converge towards optimal behaviour, while the other is concerned more with process accuracy than optimality.

Learning can be conscious or non-conscious. Non-conscious learning tends to be associated with unimportant and well-known situations, whereas conscious learning is associated with important decisions. Brenner (2006) summarised the use of learning models under various situations as shown in Figure 3.2. With non-conscious learning, behaviour that leads to better results tends to increase in frequency. Examples of this type of model are included in the Bush-Mosteller model, the principle of melioration, and the Roth-Erov model.

Figure 3.2: Steps to choose an accurate learning mode for representing decision making (Brenner, 2006)



Conscious learning can be divided into routine-based learning and belief learning. In routine-based learning models, there is a direct connection from an agent's experiences and observations to their behaviours. Routine-based model can be at population or individual level. At the population level, the models assume that human behaviour adapts towards better outcomes. Most of the models of this type originate in biology, e.g., replicator dynamics, selection-mutation equation, evolutionary algorithms, and reinforcement learning. At the individual level, the models assume that conscious learning processes have different features, some of which dominate in some situations. For example, some people dealing with a new problem like to watch others then mimic successful behaviour. Four features are often used: experimentation, experience collection, imitation and satisficing.

Belief learning is another kind of conscious learning, in which individuals develop a mental model about the state, dynamics and interrelations of their environment. Beliefs are not directly observable, but brain processes are increasingly described in computational economics, including artificial intelligence and machine learning. Existing belief models include Bayesian learning, which is a prominent optimal learning model that assumes people optimise their behaviours, and least squares learning, in which people make assumptions and optimise their behaviour. Many other learning/optimising processes may fall into this category, for example, genetic programming, classifier systems (people tend to sort things, events and relationships into classes and act according to their classification), neural networks, rule learning (cognitive learning also follows the rules of reinforcement learning) and stochastic belief learning.

3.1.3 Opinion formation

Opinion formation plays a vital role in day-to-day lives and as such there has been a great deal of research in the area over the years.

In an agent-based model, opinion formation and information transfer are closely related (Wu & Huberman, 2004). An agent must first amass information before opinions can be formed. In the context of an agent-based model, it is common for a proportion of the information to come via other agent in the system. Thus, a great deal of the literature relating to opinion formation also contains aspects of information transfer. For this section, opinion formation is defined as a specific process of information utilisation both by individuals and groups.

Models of opinion formation among communities of agents are among some of the earliest attempts to model complex systems (von Neumann, 1966) and are tied closely to early information/diffusion theory (Turing, 1952). The majority of these models have been continued to be based on cellular automata (one or two dimensional) and have been developed to examine tipping points around community level opinion formation covering issues such as the drivers of ethnic segregation (Schelling, 1971) and cooperation (Axelrod, 1984, 1997). With the advent of modern computing, these early models were used to analyse other real world phenomenon from standing ovations and product adoption through to rioting and civil war (von Neumann, 1966). Later work has modelled political attitude in a two dimensional continuous space based on 'traits' of personal and economic freedom, and linked the personal attitudes to the society's ability to reach consensus (Sznajd-Weron & Sznajd, 2000).

Macro level opinion formation and the underlying micro level behaviours are tied into a feedback loop whereby an individual's opinion is both driven by and forms part of the macro level opinions (or social norms). In its simplest form, the sharing of these opinions can be described as a model of knowledge diffusion.

These opinions play an important role in three key drivers of an agent's behaviour:

- Preferences, such as conforming to social norms;
- Perception of future performances of both self and society; and
- Opportunities, e.g. to improve one's relative position in society.

Boccaletti et al. (2006) summarised a number of network models for simulating the process of how a consensus emerges out of initially different opinions in a group of agents. In addition to the Sznajd-Weron & Sznajd (2000) model above, these include:

1. Deffuant et al's (2000) model: The difference between the opinions of two agents will be reduced when they communicate if the difference is smaller than a threshold; otherwise, their opinions remain unchanged. If the threshold is < 0.5, all agents' opinions will converge; otherwise, they will emerge into two groups.
2. Hegselmann & Krause's (2002) model: The opinion of an agent (chosen randomly) is changed into the arithmetic average opinion of the all agents in a time-step. It may lead to many groups of different opinions.

A number of other models can be used to describe various forms of information transfer such as epidemic spreading (unwilling transfer), rumour spreading or diffusion of innovation (willing transfer) (Boccaletti et al., 2006). Game theory has also been used to simulate interactions among decision-makers (e.g., Osborne, 2002).

3.2 Decision-making

Many approaches exist to represent decision making in MAS models in the land-based sector, but they can be divided into two categories: behaviour heuristics and optimisation (Schreinemachers & Berger, 2006). The economic literature generally recognises a similar division in modelling decision making in other contexts. This section covers examples of both types of decision making in models.

It should be noted that there is a continuum between heuristic and optimising behaviour combined in MAS models (Schreinemachers & Berger, 2006). For example, in an optimising model, heuristics can be used to constrain the range of perceived decision alternatives, so as to reduce search and computational cost.

3.2.1 Behaviour heuristics

Much agent decision making in abstract as well as empirical MAS has been represented as behaviour heuristics. Behaviour heuristics is advocated mostly by psychologists and cognitive scientists, based on the empirical evidence that has shown that people use simple heuristics to make decisions. In addition, these researchers often argue that the neoclassical economic model of utility maximisation is infeasible because of its informational and cognitive processing requirements.

Most heuristics build on the concept of bounded rationality (Simon, 1955, 1991), which refers to the limited cognitive capabilities of humans in making decisions, described as a search process guided by rational principles, that is, a process of satisficing (blending satisfied with sufficing). Since decision-makers lack the ability and resources to arrive at the optimal solution, they instead apply their rationality only after having greatly simplified the choices available. Thus the decision-maker is a satisficer seeking a satisfactory and sufficient solution rather than the optimal one. In rural systems, farmers typically use a large number of heuristics in decision making, perhaps because of the great uncertainties of natural phenomena (uncertainty about future outcomes combined with a lack of measurability of past outcomes).

The MAS model with cognitive agents is sometimes described as a belief-intention-action architecture (Bousquet & Le Page, 2004). That is, an agent has a belief (which is always being updated), and uses the belief to examine all the available options for actions, selects an option as an 'intention' and acts when needed.

Heuristics are implemented in MAS models using decision trees. They are intuitive and mostly simple rules, also called 'condition-action rules', 'stimulus-response rules', or 'if-then rules'. These rules are easy to validate by interacting with farmers and experts. Its implementation needs the modeller to identify (1) important decisions, (2) correct sequence of decisions to be made and (3) saturation level for decisions. That is, the modeller needs to know not only the decisions that agents need to make, but also the number of options at a decision making level, and the criteria that decision-makers use to chose one option instead of another. These criteria can be determined by various methods, such as sociological research, data-mining of survey data, participatory modelling and role-play games, laboratory experiment and group discussions (Schreinemachers & Berger, 2006). For further discussion on systems modelling methodologies and the inclusion of stakeholder in model development, refer to Blackett (2009).

An example of the application of heuristic decision making is Manson (2000), which focused on modelling a variety of decision-making strategies for these agents. Three different decision-making models were tested:

- simple heuristic models, such as, 'use land near road for three years then leave fallow';
- a subsistence-oriented model whereby agents use information about each cell's agricultural suitability and distance from market to determine the location and production type necessary to feed the household; and
- genetic programme models, 'calibrated by matching actor land-use histories to an array of decision variables from the smallholder survey and GCA grids' (Manson, 2000, p. 6).

The detail in the model allowed the research to incorporate a great deal of empirical data regarding soil, land use, etc. In addition, by including two types of agents, the model simulated the activities of both institutions and smallholders, allowing an assessment of the original theoretical model.

Modelling heuristic decision making has several weaknesses. One issue is the lack of information for alternatives. Another issue is the difficulty of coping with large numbers of rules and with heterogeneity in system inputs and outputs (Schreinemachers & Berger, 2006). In addition, it may be necessary to develop rules for the choice of decision rules, which sets up an impossible backward induction problem (Hey, 1982).

3.2.2 Optimisation

Many MAS models in land-use research use optimisation in decision-making. Optimisation can be used for a normative purpose to re-allocate resources to better uses by eliminating inefficiencies, or for a positive purpose to replicate or simulate an observed resource allocation.

In contrast to the bounded rationality in behaviour heuristics, it is assumed that decision-makers are rational optimisers with foresight. They are able to process large amounts of information on all feasible alternatives and select the best one. Optimisation models can be calibrated to the observed behaviour by carefully representing all the opportunities and constraints in the model (Schreinemachers & Berger, 2006).

One of the attractions of optimisation is its mathematical tractability. Optimisation in decision-making can be implemented in a MAS model using a variety of approaches, some of which are discussed below.

Mathematical programming

Mathematical programming is widely used in optimising and decision-making in MAS models in the land-based sector (e.g., Balmann, 1997; Becu, Neef, Schreinemachers, & Sangkapitux, 2008; Berger, 2001; Happe et al., 2004). This approach involves constructing objective functions for various activities, such as for cash income, food, leisure time, nitrate leaching, or greenhouse gas emissions. The functions are also subjected to various constraints, which may be in dollars, time, or other units. The objective function is then maximised subject to the constraints, which produces the best solution to the model. Agent heterogeneity may be represented by modifying the objective functions or the constraints.

Some advantages of mathematical modelling are that it can:

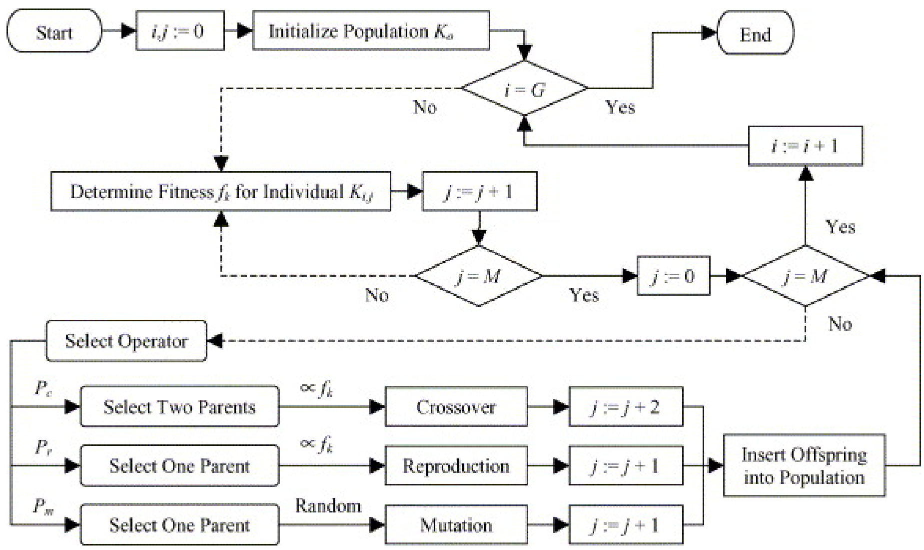
- represent heterogeneity, such as farmer personalities and farm conditions;
- incorporate a large number of decisions in a single model;
- capture economic trade-offs in resource allocation because it considers various decisions simultaneously; and
- assess the quantitative impact of policy interventions.

The main drawback to mathematical programming is that all information in the model must be represented numerically. It can be a challenge to integrate insights from qualitative research into a mathematical model.

Genetic programming

Genetic programming is an evolutionary algorithm-based methodology inspired by biological evolution to find computer programs that perform a user-defined task. It is used in various complex optimisation and search problems. The SYPRIA model by Manson (2005) used genetic programming in modelling decision-making for assessing effects of land-use policy changes. It specified a response variable (agricultural land-use in 1992) as a function of a set of predictor variables (1987 environmental and institutional variables) chosen for their effects as hypothesised by land-use theory. A total of 3200 agent decision-making strategies were sampled over 100 Monte Carlo runs in order to understand how environmental and institutional factors influence actor decision-making (essentially a multi-criteria evaluation).

Figure 3.3: Genetic programming from Manson (2005)



The basic process of genetic programming (Figure 3.3) is to construct the initial population of agent strategies, called programmes. Individual programmes in generation K_i are parents to offspring that constitute the following generation K_{i+1}. The population programmes at K_0 are randomly constructed, but each succeeding generation becomes better because individuals create offspring via three operators:

1. crossover (breeding) – trading portions of two parents to create two offspring programmes;

2. reproduction (cloning) – placing a duplicate of a parent into the next generation for coherence of strategies across generations; and

3. mutation – random changes to parts of a parent to create a new offspring programme.

The weaknesses of genetic programming are the subject of continuing research because they can be difficult to interpret and there are dangers in conflating human decision-making with biologically inspired models of computer programming (Manson, 2005).

Artificial neural networks

Artificial neural networks are a data modelling tool capable of capturing and representing complex input/output relationships. Development of neural network technology stemmed from the desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. Neural networks resemble brain function in that they acquire knowledge through learning, and store the knowledge within inter-neuron connection strengths.

The most common neural network model is the multilayer perceptron, also known as a supervised network, which is used to approximate functions. It requires inputs paired with desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data with the goal of using the model to predict future outcomes. Neural networks learn using an algorithm called back-propagation (training). In this process the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back to the neural network and used to adjust the weights such that the error decreases with each iteration, and the neural model gets closer to producing the desired output after each iteration. Optimisation using neural networks has been used in modelling intelligent ant communities (Bousquet & Le Page, 2004).

A limitation of neural networks is that they are trained in specific problem solution spaces. The model is constructed from purely *a priori* knowledge. If the problem solution space changes over time, i.e., if the rules of the game change, the training may not be appropriate for the new situation.

3.3 Risk

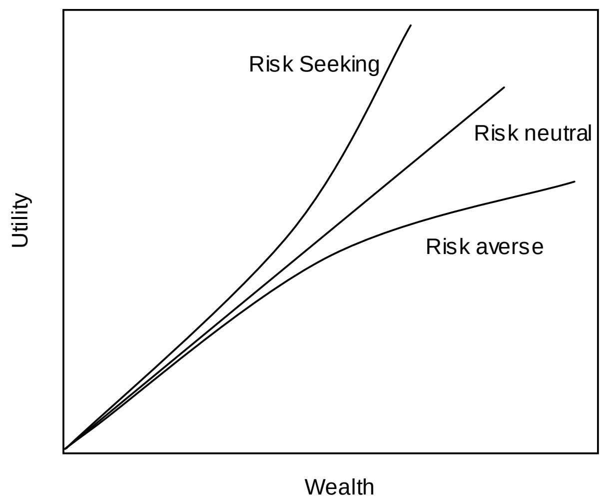
This section considers the incorporation of risk preferences and personality traits into the decision-making of the agents. This topic does not appear to be a well developed area of agent-based models in agriculture. There are a few papers that have modelled risk in their agents, thus these equations could be used to construct agents with different levels of riskiness.

Lettau (1997) defines riskiness in his agent based model by defining risk aversion using the following equation:

$$U(w) = -\exp(-\gamma w) \qquad (5)$$

In this equation, the utility (U) of a given unit of additional wealth (w) decreases as greater levels of wealth are attained; there is declining marginal utility of wealth. In this way, the baseline for riskiness in the model is somewhat risk averse. The riskiness of an agent can then be manipulated by varying the value for the coefficient on wealth, γ. In absolute terms, an empirically risk neutral agent would have a linear relationship between wealth and utility. Risk seeking agents then, would have a curvilinear relationship wherein higher levels of wealth would lead to even higher levels of utility (See Figure 3.4).

Figure 3.4: Riskiness as a function of the relationship between wealth and utility



Lettau's (1997) equation can be compared to Hoffmann, Kelley, and Evans (2002) who provide the following equation:

$$E(u) = E(w) - \alpha\sigma^2{}_w \qquad (6)$$

In this equation, expected utility ($E(u)$) is derived from expected wealth ($E(w)$) minus a second term representing risk aversion (α), multiplied by the variance of wealth ($\sigma^2{}_w$) to represent random changes in wealth. Thus, this equation accounts for agents' desire to limit random variations of their wealth. That is, the second term in the equation accounts for people's preferences for more stable sources of income.

Risk preferences of agents can also be expressed through the choice between an asset which varies in uncertainty and an asset with a fixed return. A number of financial models have modelled simple markets in which agents choose between two types of assets. For example, Grossman and Stiglitz (1980), created a hypothetical market in which one asset had a fixed dividend and a second asset had a dividend (u) defined by the following equation:

$$u = \theta + \epsilon \qquad (7)$$

In this equation θ is a random variable which is observable at a cost and ϵ is a random variable which is unobservable. Thus, there are two types of hypothetical individuals in the authors' model, those that purchase information and those that rely only on the price of the risky asset. The authors also include an equation defining risk by using the utility function ($V(W_{li})$) defined as:

$$V(W_{li}) = \text{-exp}(-aW_{li}),\ a > 0 \qquad (8)$$

In this equation, a is the coefficient for risk aversion and W_{li} is the individual's wealth, determined by the following equation:

$$W_{li} = RM_i + uX_i \qquad (9)$$

R, in this equation, is the return on the risk-free asset, and u is the dividend of the risky asset, while M_i and X_i represent the amount of risk-free and risky assets held by the agent.

Another example of a market in which a risky and risk free asset are modelled can be found in LeBaron's (2006) presentation of his work with the Santa Fe Artificial Stock Market (earlier descriptions of the Santa Fe Artificial Stock Market can be found in Arthur et al. (1997) and LeBaron, Arthur & Palmer (1999)). In this hypothetical market a risk free asset is given the return (R) and a risky asset's dividend d_t is:

$$d_t = d + p(d_{t\text{-}1} - d) + \epsilon_t, \qquad (10)$$

where ϵ_t is Gaussian, independent and identically distributed and p is set to 0.95. In addition, this model used a sophisticated learning and forecasting model. Agents use forecasting equations to try to predict the future price of a risky asset. At the end of each period, agents have a probability (p) to change their current set of forecasting rules (p is a parameter set for each model run). Learning for an agent starts with the worst performing 15 per cent of the agent's forecasting rules being dropped. These are then replaced using a modified genetic algorithm with both crossover and mutation. During crossover, parts of rules are swapped for the different parts of an existing rule. In the course of mutation, parts of a rule are changed randomly and thus result in a rule that might not be present in the rest of the population.

Risk and other forms of 'personality' that can be imbedded into agents' behaviour highlight the benefit of an agent based model as a whole because they allow for the creation of variables which allow for more accurate modelling of real world phenomenon by mimicking the behaviour of actors in the real world. Modelling the riskiness of agents can allow for emergent properties based on different forms of riskiness to develop in the model.

Once a decision has been made as to which equation to use to define riskiness, it is a simple step to generate heterogeneous agents by either randomly or empirically assigning different values for the modifying coefficient or exponent. Defining and manipulating the riskiness of agents allows the modeller to use risk to drive different processes in a model.

3.4 Summary

A key driver in the decision-making process of agents is the information transfer among the agents that occurs through a social network. This information transfer can be explicitly modelled to introduce new information and technology adoption and to represent heterogeneous behaviour of the agents as a function of social influence. An agent's responses to new information and opinion formation can be modelled by using appropriate network dynamic models. Although information transfer is difficult to validate, it is one of the core components in MAS models. In addition, several models have been developed to simulate agent-learning. Learning can be either conscious or non-conscious, whether the decision is important or not.

Opinion formation among agents is a well developed research area. For the development of a MAS model in New Zealand, opinion formation is an important process as it is closely related to information transfer: the collection of information precedes opinion formation.

There are several approaches that have modelled decision-making in MAS models. These can be put in two categories: behaviour heuristic and optimisation. More behaviour heuristics should be used if the model is used by social, economic and environmental policy makers to explore the farmers' actual responses to institutional and environmental changes. On the other hand, if the model is to provide a tool or modelling platform to support farmers in making decisions when faced with economic and environmental changes, incorporation of optimisation algorithms can be useful to help users achieve maximum performance with regard to some criterion.

An underdeveloped research field in the context of modelling agent's behavior in MAS models for the agricultural sector is the incorporation of risk preferences of agents, e.g. farmers. However, the literature on financial model or computational economics provides examples of approaches that could be applied to agriculture.

Chapter 4
Model-level Issues

The previous chapters considered some of the components of a MAS model for New Zealand's pastoral industries. This chapter discusses some of the challenges that arise when the model is considered as a whole. Some of the challenges discussed are the time-step of the model, market behaviours, and verification and validation of the model.

4.1 Time-step of the model

An important modelling issue is the time-step of a model. In a MAS model, a decision or action happens and affects the decision environment. The change in the environment is then fed back into a next decision or action. The time span between two actions is the time-step. The appropriate length of the time-step is related to the use of the model as well as the characteristics of the data.

In empirical MAS models simulating land-use changes, an annual or seasonal time-step is generally used (Manson, 2005; Schreinemachers & Berger, 2006)(Schreinemachers & Berger, 2006). For example, in modelling decision-making of farm agents, Schreinemachers & Berger (2006) used a three-stage process of investment, production and consumption in an annual cycle. Decisions on-farm happen in different time cycles, and also depend on the type of commodity produced. Some decisions are relatively long-term, such as the decision to plant trees. Other decisions are more short-term, such as those regarding pruning and spraying of trees, or stocking and slaughtering of animals. The appropriate time-step will thus depend in part on the system modelled and the types of questions that will be analysed within the model.

It is possible to include different intervals of time for different aspects of a single model. For example, it is possible to embed a daily time-step biophysical model for predicting crop production into a seasonal time-step model to simulate agent behaviour on farm. Using a time-step appropriate for the decision making at issue, but avoiding unnecessary iteration, allows good model performance.

4.2 Market behaviour

Markets can be a key institution in a MAS model. They were discussed in Chapter 2 in the context of productive resources, but the same discussion applies to markets for the commodities produced by farmers. In many agricultural models, each time-step is associated with a transaction, such as a market transaction between buyers and sellers or an agreement between landowners and agents using the land. Transactions for productive resources affect how they are allocated across the agents in a model, and transactions for commodities produced affect how successful the agents are. Six mechanisms could be used to simulate commodity markets:

- external commodity prices,
- cobweb model of a market,
- calculation of a market clearing price,

- order books,
- resource transfer through direct contact between agents, and
- auction.

At the end of a time-step, when resources have been allocated and agents have made their production decisions, the market mechanism then operates to provide commodity prices. These prices then become part of the agents' experience, and can influence the decisions in the next time-step.

Markets are thus a part of a MAS model where agents interact with each other. This interaction may be direct, as when an agent must make a direct transaction with another agent. It can also be indirect. This is the case, for example, when all agents offer their products on the market and the final price is determined by the aggregate amount of product offered. In addition, markets can influence the cellular automata in a MAS/CA model. If an agent has a choice over the use of a specific grid cell, then the experience in the market can influence the agent's choice. In this way, the use of resources in future time-steps can be affected by earlier market solutions.

4.3 Verification and validation

Model verification and validation are important in the development of a model. They help with the credibility and acceptance of the research with end-users, and they also ensure that model results are based on sound scientific knowledge (Bousquet & Le Page, 2004; Midgley, Marks, & Kunchamwar, 2007; North & Macal, 2007). Midgley et al. (2007) provided an explanation of the terms: 'If verification is solving the equations right, then validation is showing that one has solved the right equations'. North and Macal (2007) explained verification as ensuring that the model does what it is intended to do from an operational perspective. They defined validation as whether a model represents and produces the behaviours of a real world system. However, the complexities in verification, calibration and validation for agent-based models are well documented (LeBaron, 2006; Midgley et al., 2007; Pahl-Wostl, 2002; Polhill et al., 2002). In contrast, the challenges with creating abstractions of human interaction are poorly defined, although participatory modelling can assist in verification in this area (Parker et al., 2003).

Pahl-Wostl (2002) explained that the combination of agent-based models and stakeholder participation leads to stakeholder-elicited knowledge and perceptions, factual knowledge from data, subjective expert knowledge and mental models. These dimensions require some form of validation, particularly with regard to plausible outcomes and the process of social learning. In the context of business MAS models, North and Macal (2007) described multiple methodologies and computational testing processes for ensuring verification test cases and model validation techniques to create acceptable results. However, the increasing complexity of MAS models generates challenges in ensuring they are credible and suitably robust. In attempts to enhance the scientific credibility of MAS models (in the absence of mathematical analytical proof abilities; Axelrod, 2006; Bousquet & Le Page, 2004), Bousquet & Le Page (2004) outlined strategies for providing rigorous presentation of the structure. They recommended that validation be undertaken by comparison of data and methods with other research, as well as by testing the relevance of hypotheses with the use of role-play games.

The challenges in both micro-level and macro-level validation suggest that both quantitative and qualitative options for validation should be considered, and that a staged validation process may be appropriate (Berger, 2001; Midgley et al., 2007). Data output may be calibrated by assessing the similarity of model outputs to other evidence (LeBaron, 2006). Parker (2007) reviewed a number of validation approaches, including regression analysis and pattern-oriented modelling, and suggested that it is important to have the right target in mind when considering how to validate a model. There is also potential for mixed methods: a combination of empirical data, pseudo-informal observations and synthetic data may be used to produce outputs falling within specified parameter ranges (Berger, 2001).

The validity and robustness of MAS frameworks and outputs is an on-going consideration in this area of research (LeBaron, 2006). There is some discussion of a need for consensus regarding protocols (Bousquet & Le Page, 2004; Midgley et al., 2007), albeit within the generic trade-off between realism and clarity or simplicity (Axelrod, 2006; Midgley et al., 2007).

4.4 Summary

When the model as a whole is considered, a number of issues become important. One technical issue is the time-step to be simulated by the model. A model will simulate a decision or action that produces a result which then influences the next decision or action. Whether the simulated time period is daily, annually, or some other period depends on the uses of the model and, as well, the available information. Importantly, producing a parsimonious model is also a consideration. A second issue for agricultural models is the method for simulating market behaviour. To simplify the representation of a market, producer might be price-takers, and the prices varied exogenously to simulate market movements. A number of more complex market procedures have been used in MAS models, including analytical solutions to supply and demand functions, auctions, and inter-agent trading.

Key considerations at the model level are validity and verification. Agent-based models that simulate human-environment interactions can become complex. In addition, an agricultural MAS model needs to represent the policy and innovations that affect agricultural systems. Increasing complexity brings challenges to ensure that the model is valid, credible, verified and suitably robust. Interdisciplinary research collaboration might be one approach to meet accurate and realistic outcome goals of agent-based models. The involvement of stakeholders, regulatory institutions, and researchers from other disciplinary fields in the development process of the model creates potential to adjust semi-structured situations and alleviates commitment to change management. The literature also suggests the use of different types of data and sources of information, increasing the potential for research from several disciplines to contribute to a single MAS model. However, there is clear scope for more consistent verification and validation methods for agent-based models.

Chapter 5
Usability and Meeting End-user Requirements

If a model is to be used by anyone beyond a core group of designers, usability of the model and the requirements of end-users need to be taken into account. 'Usability' is a term to denote the ease with which people employ a particular tool in order to achieve a particular goal; 'user-friendly' is often used to mean the same thing. The focus of this chapter is designing a model that helps end-users achieve their goals or objectives. The emphasis is on the usefulness of the system framework rather than technical proficiency with the software.

Gould (1988) discussed four key points in the usability design process:

- focus on users,
- empirical measurement,
- iterative design, and
- integrated design.

These points are the basis for the present discussion of usability, which is divided into two categories: system usefulness and processes to meet user requirements.

5.1 System usefulness

In the context of policy-relevant environmental research, McIntosh et al. (2007) discussed problems in end-user uptake of support tool technology and the incorporation of outputs into practice. They demonstrated the absence of integrated and policy-relevant operation of support tools in actual policy work. With regard to this problem, they argued that research papers on decision support systems and models refer more to the development and application of tools, rather than the use of tools and models by stakeholders such as policy or planning organisations. A key issue appears to be the usability of tools and models by groups other than the developers. McIntosh et al. questioned whether developers understand what users actually want, need or can utilise when developing tools. They argued that a better approach is more oriented towards users than developers.

Díez and McIntosh (2009) identified factors that influence the usefulness of information systems[4]. These factors give advice on managing system development and implementing processes.

- A useful information system supports collective action through the relationship network amongst technological attributes, individual users and organisational tasks.
- The best predictor for pre-implementation processes for an information system is user participation, with success and user satisfaction the two dependent variables or process outcomes.

[4] Computer-based information systems are tools for the storing, recording, processing and dissemination of information to support purpose for groups involved, and include computational software tools such as simulation models and decision support systems (Checkland & Holwell (1999) as cited by Diez & McIntosh (2009)).

- The best predictors for implementation processes are perceptions of early adopters including ease of use and compatibility or usefulness.
- The only dependent variable after the implementation is success[5] (user satisfaction).

The policy and management results of the Díez & McIntosh (2009) review are transferable to other disciplines. There is the strong suggestion that failures in information system uptake may be a consequence of failures in the implementation process (Díez & McIntosh, 2009). Indeed, McIntosh et al. (2007) argued that computer-based support tools are currently too focussed on technical concerns, where a greater emphasis of contextual and social aspects is required to increase end-user acceptance. Díez & McIntosh (2009) observed a limited uptake of computer-based decision support tools by the agricultural community, especially from farmers. This was seen as a special case within the general problems of adoption and diffusion of information systems. However, the key variables recognised for a general usefulness of information systems by Diez & McIntosh are very similar to parameters for user acceptance in McCown (2002).

The next section discusses the usefulness of agricultural and land-use based decision support systems (e.g. Kerr, 2004; McCown, 2002). This provides a background regarding these tools and extends the lessons regarding usefulness to agent-based models.

5.1.1 Decision support systems

The benefits from decision support systems are an improved system analysis and an understanding of processes. These constructs are well suited for stakeholder engagement and policy formulation (e.g. see Díez & McIntosh, 2009; McCown, 2001). However, the translation from potential to actual use remains a concern (Hayman, 2004; McCown, 2002; McCown, Brennan, & Parton, 2006). The scepticism is especially focused on the interpretation of broader system modelling, such as simulation modelling to support farming systems innovation (see Woodward, Romera, Beskow, & Lovatt, 2008). There have been considerable efforts to design decision support systems in agriculture to assist decision-making by farmers. The uptake and on-farm usage of these systems, however, was low and included many failures (see Hayman, 2004; McCown, 2002). This poor engagement with end-users has occurred even though the software systems have been well developed and farmers have had computer access (Kuhlmann & Brodersen, 2001; McCown et al., 2006). One interpretation is that the lack of uptake implied that the modelling paradigm used was not relevant for on-farm application (McCown et al., 2006). While a common critique is that models are only partial representations of reality, McCown et al. (2006) explained that it is necessary to focus on the use of a model as a *tool* for complex farm management rather than seeing the tool as a *proxy* for a managers' decision-making. This subject has been advanced by McCown and colleagues in recent years who gave evidence for the role of decision support systems as a tool in a modified decision process. In this context, McCown et al. (2006) concentrated on the credibility and adoption gap existing between science-based decision support and practical farming (McCown, 2002).

In contrast, Walker et al. (2001) argued for functional design in the development of decision support systems. Within a pragmatic approach, they used adaptive management principles to propose adaptive decision-making based on the integration of research outcomes with stakeholder requirements. In this context, Walker et al. (2001) used integrative methodologies

[5] Whilst there are multiple definitions for 'success'; within the context of this review, success is a 'system that satisfies certain quality criteria (cost-effectiveness, ease of use, software capabilities) and user requirements, including provision of added value to user not available before (Díez & McIntosh, 2009).

which were novel in decision support systems. A recent comparable methodology is the 'end user enabled design environment' (EUEDE; Miah, Kerr, Gammack, & Cowan, 2008). The EUEDE focuses on the environment around the construction of the decision support system, by engaging domain experts for the creation of a knowledge base with end-users (e.g. farmers). This knowledge base is then used for the specific decision support system. The derivation of decision-making rules from a knowledge base provides the data process for decision-making and underpins the EUEDE architecture (Miah et al., 2008, pp. 898, Fig. 6).

The promise of decision support systems as a useful methodology for on-farm decisions was captured by Hayman (2004). He stated that computational models are beneficial for farmers to use in operational management. In addition, Hayman explained that farmer decision-making is limited by information and procedures, and that tactical on-farm decision-making is the appropriate intervention point for decision support systems. However, the review by Hayman (2004) clarified that on-farm computer model use (with operational management bias) would be more an educational and learning tool (see also McCown, 2002). The target for information transfer becomes the consultant who uses the decision support systems and simulation tools, rather than the farmer (see also Carberry et al., 2002). Hayman also pointed out that the suitability for strategic or tactical intervention interacts with the user's assumptions, whether that user is an expert or novice. In this context, suitability is compromised of complexity and interpretation (see also McCown, 2001). Indeed, Woodward et al. (2008) argued for jointly created (modeller and client) whole farm simulation models. These models use decision rules to specify alternative management strategy options. A difficulty is that different stakeholders have different perceptions of system complexity. The multiple input criteria and the dynamic nature of farm systems make their use look even more difficult (Woodward et al., 2008). However, Woodward et al, (2008) described an improved farm system simulation methodology. The method includes iterative client involvement at each development stage and appears to be a feasible option for improved farm system decision support tools.

Despite the challenges for using decision support systems in the agriculture sector, particularly where the farmer is the end-user, there are also areas of success. The following examples reflect the importance of the relationship between the developer of the decision support system and the potential user. A shift from prescribed action to facilitated learning for both parties is discussed (McCown, 2002), and clients are involved throughout the model innovation process (Woodward et al., 2008).

One example is a nutrient management model for dairy farmers in North America, the Dynamic North Florida Dairy Farm model (DyNoFlo; Cabrera, Breuer, & Hildebrand, 2008), which represents a whole-farm decision support system. This model includes environmental, economic and bio-physical components based on the collaborative development process with many stakeholders (e.g. farmers, researchers, consultants, regulatory agencies). The feedback from different sources and the iterative development approach is expected to support the longevity of model acceptance and adoption (Cabrera et al., 2008). The system also benefits from an underpinning robust and sound science, and from peer-validated model development technique and protocols (Woodward et al., 2008). Another example is an investigation of decision support intervention on dryland cropping farm communities in North Eastern Australia (FARMSCAPE, Carberry et al., 2002)[6]. This work has illustrated a successful approach for guiding the development and delivery of multiple decision support systems to farmers and stakeholders. This is a participatory research framework, aided by focusing on crop consultants as end-users. The approach links the science-based research and the farmer as decision maker. A third example considered the incorporation of decision support systems

[6] Farmers', Advisers', Researchers', Monitoring, Simulation, Communication And Performance Evaluation.

to simulate alternative animal waste management strategies on Reunion Island (Aubry, Paillat, & Guerrin, 2006). The research used a conceptual representation based on synthesised farmer knowledge and practice. The active human input into the model is encapsulated as structural and management variables. The decision rules are based on real world information collated over a period of time. A final example is Kerr (2004), who analysed the development of a knowledge-based decision support system for the Australian dairy industry (KBDSS; DairyPro). He found that developers needed ‘a good working knowledge of the target industry’ and processes to ensure they ‘understand the types of decisions made’ by end-users – in this case, farmers (p. 127). The DairyPro model appears to have distinctive characteristics. It is strategic rather than tactical. In addition, ‘domain experts’ were used for this data, rather than having production parameters derived from mathematical or simulation model runs. End-users contributed to the development process for ‘ownership buy-in’ that was an aid to the design of the model (Kerr, 2004). However, Kerr and Winklhofer (2006) noted that when challenged by an external change such as dairy deregulation in Australia the recommended approaches to the development of the ‘DairyPro’ model were no longer valid. However, a re-assessment of the model and consultation with stakeholders and end-users resulted in adaptation. The model then appeared suitable in the newly deregulated environment. However, the authors did note a relatively low model use and uptake (Kerr & Winklhofer, 2006).

Within a New Zealand pastoral context, and with reference to the uptake of the OVERSEER (Wheeler et al., 2003) nutrient management tool uptake, D. Wheeler (pers. comm.) identified the benefit of having a specific user group with defined requirements, alongside a specific need, such as evaluation of environmental impacts and mitigation. With regard to cropping nutrient management in New Zealand, Li et al. (2007) outlined the development of a set of simulation-based crop calculators. These calculators were developed from an initial simulation tool into usable decision support tools. The incorporation of domain knowledge from growers was necessary to have accurate or credible simulation of soil dynamics and crop growth. In general, it was necessary to incorporate a user-friendly interface, to keep the tool as simple as possible, and to offer support in the use of the tool (Li et al., 2007).

As recognised for example by McCown (2002), the criteria for usefulness of a decision support tool depends on the end-user, e.g. farmer or middle level organisation manager. It also depends on the motivation for use, such as regulatory or voluntary. If an end-user is a decision-maker with discretion to choose and power to act, a decision support system must add value by enhancing the decision process. In addition, model developers need to recognise that intervention must be feasible. They need to recognise that behaviour occurs in an internal social context and external material context within a shared culture (McCown, 2002). The paradigm shift of both acceptance of an end-user participatory process in model development, and the added social dimension in the decision simulation modelling, has made the agent-based model approach a promising complement to existing system modelling (Pahl-Wostl, 2002).

The issue of whether a decision should be complex or simplified appears contentious. Where end-users perceive complex real-world dynamics, they may question the reliability or trustworthiness of simpler models (see Kuhlmann & Brodersen, 2001; Tesfatsion, 2006). However, there is also an argument for simplified strategic scenario-based models that are underpinned by a top-down approach based on expert knowledge (Kerr, 2004). The variation in approaches can be related to the objectives of different models and the specific end-users that are identified, be they policy analysts, planners, farm managers, etc. (Happe & Balmann, 2007).

5.1.2 Agent-based models

Axelrod and Tesfatsion (2006) noted specific goals for agent-based model researchers such as empirical understanding, normative understanding, heuristic knowledge and methodological advancement. These research groups appear to differ on whether simple or complex agent-based models are desirable. The 'simple' model group focuses on clarity with broad generalisations regarding domain specific systems, whereas the 'complex' model group seeks to represent complex systems with detailed domain-specific results as the ideal. North and Macal (2007) take the pragmatic view that both approaches are plausible and equally valid, but the system being modelled is the important motivator. Certainly, with regard to the dynamic bio-physical systems of agri-ecosystems and land-use integration modelling, complex system modelling appears a dominant option to meet goals (see Happe et al., 2004; Matthews et al., 2007; Parker et al., 2003).

Agent-based models may be useful for assessing complex adaptive systems and integrated land-use management (refer Berger, 2001; Bruun, 2004; Matthews et al., 2007; Midgley et al., 2007; Parker, 2007; Tesfatsion, 2006). The main advantages over conventional modelling are aggregated individual decision-making, emergent behaviour from micro- to macro-level, and heterogeneous interactive agent behaviour within complex environments. While the use of MAS models for managing business complexity is preferred by North and Macal (2007) as a new modelling paradigm for practical decision-making, this enthusiasm is not shared by all researchers in agent-based computational economics and agent-based land-use models (refer Axelrod, 2006; Matthews et al., 2007; Parker, Hessl, & Davis, 2008). Issues with the acceptance and usability of decision support systems at the farm level have been noted by the agent-based model researchers. Although challenges exist for the adoption of agent-based models, the outlook for their use for modelling complex systems (such as integrated land-use) appears promising (Matthews et al., 2007). In particular, their usability can be enhanced through collective learning (Barnaud et al., 2008) and recognition of the diverse needs of end-users.

5.2 Processes to meet user requirements

Failures in the implementation process have been noted for information systems in general (Díez & McIntosh, 2009) and for agricultural-based decision support systems in particular (see Hayman, 2004; McCown, 2002). These errors/malfunctions suggest that the information and credibility gap between model developers and stakeholders or end-users requires bridging, for example through interaction in an iterative modelling process (see Díez & McIntosh, 2009; Janssen, Hoekstra, de Kok, & Schielen, 2008; Kuhlmann & Brodersen, 2001). However, successful model application has been associated with active end-user participation in the process (see Carberry et al., 2002; Li et al., 2007; Woodward et al., 2008). Participatory approaches are seen as a feasible linkage technique that allows a combination of factual knowledge and analytical capacity with end-user knowledge and subjective perception (Pahl-Wostl, 2002). This is formalised as participatory modelling (e.g. Cabrera et al., 2008).

Janssen et al. (2008) provided a framework of interactive development by modellers and users. Within this model they recognise that a trade-off in model complexity and simplicity exists. In addition, Janssen et al. (2008) saw benefits in deploying the model prior to implementation, in an approach that complements both social learning and participatory modelling (Cabrera et al., 2008; Pahl-Wostl, 2002). He showed that concepts and processes exist to help match expectations and bridge credibility to achieve more successful outcomes when model-stakeholder gaps are unavoidable (see Becu et al., 2008; Kuhlmann & Brodersen, 2001).

5.2.1 Participatory modelling

Certain practices, such as participatory methodologies, have been shown to be effective in fostering the adoption and ownership of decision support systems by stakeholders. These methods have practical challenges and considerations with the people-model interface such as individual idiosyncrasies, cultural and institutional environments, and demands on stakeholders' time (Herron & Cuddy, 2007). In addition to these challenges, the budgetary cost of participatory engagement in modelling cannot be overlooked (Hayman, 2004).

For successful model development and adoption, and also to assist problem solving, participation and involvement of users and other stakeholders in projects are encouraged (Kerr & Winklhofer, 2006). This user participation can be accomplished in the form of cross-functional project teams, steering groups and project champions, where stakeholders are defined as 'an individual or group of individuals or organisations with a common interest' (Harrington, Conner, & Horney, 2000). It is noted that while stakeholders may have common interests, differences in information use or criteria for importance of information exist (Harrington et al., 2000). Other important parameters for participation are the composition of teams of importance to project outcomes and the group dynamics (Kerr & Winklhofer, 2006).

Where sociological factors and human integration are considered significant for user adoption, the development of decision support tools needs to take them into account (McCown, 2002). The employment of a participatory approach to investigate farmer valuation of decision support system tools and cost-effectiveness of delivery has been investigated, for example, with dryland cropping farmers (Carberry et al., 2002). Key methods included introducing consultants as trained model users, on-farm research, discussions around the simulation, and participatory involvement of end-users and stakeholders in model development and adoption (Carberry et al., 2002). Long evaluation processes (over ten years for the systems research team) with users and stakeholders has shown the importance of feedback, and also the iterative progress from real to abstract thinking (Carberry et al., 2002). Some difficulties that FARMSCAPE encountered were the failure of the project team to deliver as specified, conflict over intervention paradigms, and initial naivety about social processes (Carberry et al., 2002).

The interactions of stakeholders within a participatory modelling process were seen as beneficial to the creation and adoption of adaptable user-friendly decision support systems. This included environmental, economic and biophysical components as they were adopted in the decision support system of dairy farm nutrient management (Cabrera et al., 2008). The incorporation of a participatory approach encompasses end-user involvement from the start of the development process of the model. It includes regular interaction and feedback during the iterative design and development of the model. In addition, it has an open dialogue and uses recognised complementary social research systems (Cabrera et al., 2008). The highly interactive process was seen as crucial for generating comments on model development, with prototype adjustment and final model feedback to stakeholders for validation, although the intensity of the interactive process in researcher and stakeholder time and effort is noticeable (Cabrera et al., 2008, pp. 399, Table 1).

An interpretative study of 38 decision support systems in the Australian agricultural sector by Lynch and Gregor (2004) has explored the relationship between user participation and system outcome. A key component of the study is the 'degree of user influence' on the design process, being a result of both type and depth of the user relationship. Higher impact of the decision support system was associated with higher levels of user participation (progressing from consultative to consensus), and greater depth in participation noted (Lynch & Gregor, 2004).

North and Macal (2007) stated that the incremental development of agent-based models enables stakeholder buy-in and the ability to progressively document return on investment in the model. Further, successive development allows for temporal model development, an iterative process and progressive model capability building with stakeholders (North & Macal, 2007). The iterative approach itself is not new to the development of agent-based models, but the emergent properties and micro-level to macro-level behaviour outcomes throughout the model building process are new components (see Bousquet & Le Page, 2004; North & Macal, 2007). Interactive policy making with agent-based models is interpreted as a mean of facilitating the effective use of models by involving model users/policy makers in the development process. Happe and Balmann (2007) observed that the development process is iterative and requires stakeholder involvement throughout the modelling steps to orient work towards the policy decision process. The use of MAS models and role-playing games seek to develop simulation models to integrate stakeholders' viewpoints (refer Bousquet et al., 2002; Happe & Balmann, 2007). Certainly, North and Macal (2007) recommended participatory agent-based model simulation to assist learning and development in a business context. Participatory modelling within land-use systems is considered an important component of model development (Parker et al., 2003).

The relationship between simulation modelling and collective decision-making within natural resource management can support adaptive management and participation in problem solving. This can be achieved by using MAS models and role-play games, and companion modelling (ComMod[7]) theory (see Barnaud et al., 2008; Bousquet et al., 2002). The potential usefulness of a MAS model is illustrated by an application to rural credit in a developing country farming community (Barnaud et al., 2008). The participatory modelling approach emphasised the model process and the intuitive representation of real systems. The resultant appropriation by local stakeholders is a sign for the usefulness of a MAS model. Becu et al. (2008) introduced a modelling approach that has the potential for a participatory modelling approach where stakeholders are directly confronted with model assumptions, simulation output interpretation and scenario options. In contrast, the companion modelling approach assumes limited stakeholder knowledge of the computer model. However, Becu et al. (2008) noted problems both in stakeholder understanding of a model as a reproduction of reality and not as reality. These were challenges in a context of social tension and power differentials, in that case, an issue of water rights between rural villages in Thailand. Nevertheless, additional analysis suggested that the sessions on the multiple participatory simulation increased participant understanding, although it was constraining on less powerful actors (Becu et al., 2008).

5.3 Summary

The reviewed literature concentrated predominantly on the development and application of MAS tools. Some authors maintained that research puts more effort in developing and describing the tools than providing useful and usable tools for end-users. The few researchers who considered usefulness in their studies report on lack of acceptance, usability and credibility of decision support systems at the farm level. There were few models that were adopted by the agricultural community; the few that were adopted also reported some failures.

For successful model development and adoption, the involvement of end-users and other stakeholders in projects is recommended. This participation would also assist problem solving. Participatory modelling provides a useful tool for involving stakeholders and end-

[7] ComMod, or Companion Modelling, is an approach involving an iterative feedback loop between researchers and stakeholders in with MAS is used as the tool to facilitate communication (Becu et al., 2008).

users at each stage of the model development process. These approaches are even more important when human and social factors need to be modelled in an agent-based model. Several approaches include participation of stakeholders and end-users in the development process of the model. This involvement helps identify the requirements of end-users and stakeholders and increases the practical usefulness of models. Participatory modelling can link factual knowledge and analytical capacity with end-user knowledge and subjective perception. Many projects reported failures in the implementation process because end-users lacked information and models were not credible. End-user participation can be seen as technique to diminish this gap of information and credibility between the developers of the model and the stakeholders. Decisions have to be taken with regard to the stage the user involvement should occur and to which degree the users should have influence on model development. However, issues of cost and time scheduling in participatory modelling within the agent-based model construct have been noted by North and Macal (2007) and Newig et al. (2008).

In summary, agent-based modelling can be an innovative approach for participatory research (Pahl-Wostl, 2002). The combination of a high degree of formalisation with participation allows important information to be included, but in a parsimonious way (Newig et al., 2008). With the increasing importance of participatory processes in land-use and natural resource management, agent-based models may be an important tool for effective participation (Newig et al., 2008).

Chapter 6
Conclusion

There is a wide variety of MAS models in the literature. They provide some guidance for creating a MAS model of New Zealand's pastoral industries that simulates strategic decisions and behaviours of individual farmers in response to changes in their operating environment, and link to the production, economic and environmental impacts of their management.

First, this review suggests that a two-part model including both a multi-agent (MAS) sub-model and a cellular automata (CA) sub-model is the most suitable for agricultural models. In this way, variables can be divided into those linked to specific locations and thus assigned to land in the CA sub-model, and those linked to decision-making and thus assigned to agents in the MAS sub-model. By overlaying the simulated agents – constructed based on primary data on farmer behaviour – on a cellular structure that represents key features of the natural landscape of New Zealand, it should be possible to investigate the emergent properties of the country's farming sector. In particular, the response of this complex system to simulated future shocks, such as policy shifts or climate change, may provide useful information for farmers, the sector, and policy-makers.

With regard to the MAS sub-model, the research indicates that agents should be heterogeneous in terms of risk preferences and the use of prior information. The MAS sub-model allows the incorporation of further decision rules or strategies that are important for modelling farmer's decision-making in New Zealand's pastoral industries, and can also allow sociological and psychological information to be included.

Regarding the CA components, most approaches modelled land spatially with variables for different production possibilities. A New Zealand model could include values for potential outputs for dairy, meat, and forestry; other possible land-uses could also be modelled. Existing models treated other resources, such as water, in very different ways. There is no clear guidance from the literature on the best approach, as each model is tailored to the research programme. Different aspects can be treated as separate elements in a model, or simply implied by the relative productivity of CA units.

Markets have also been modelled with varying degrees of complexity. In a New Zealand context, with most commodities exported, production from various land-uses can be sold based on prices determined exogenously from a simple demand schedule.

With regard to modelling decision-making it can be either modelled using simple rules of behaviour heuristics, or using optimisation algorithms, or a combination of the two. Selection of the approach depends on the questions the model is designed to answer, with the targeted model users in mind. More behaviour heuristics should be incorporated if the model is used by social, economic and environmental policy makers to explore farmers' responses to institutional and environmental changes. Conversely, if the model is designed to support the decision-making of farm managers, the incorporation of optimisation algorithms can be useful to help farm managers expand their bounds of rationality and make informed decisions ahead of economic and environmental changes. Information transfer among the agents can be explicitly modelled both to introduce new information and technology adoption as well as for heterogeneous goal setting/measurement of the agents as a function representation of social influence. An agent's responses to new information and opinion formation can be modelled by using appropriate network dynamic models.

A clear indication from the literature is that modelling can range along a continuum of levels of detail; the key choices in modelling are both the overall level of detail desired and the level of detail desired for each given variable. Therefore, the beginning of the modelling process needs to address the twin questions of, 'what are the end goals?' and 'which variables are key to a model that approaches those end goals?' Each component of the model could be addressed using techniques ranging from the simple to the complex. These questions can help focus the research on which variables are most important and the required complexity in the model. It is also important to keep in mind that increases in model complexity also carry associated increases in error and uncertainty.

Usability is a key concern of practical modelling meant for end-users in agriculture and policy. Decision support system models and simulation models used to date in agriculture have had several issues, including connecting to existing farming practice. A model could be both successful in technical modelling terms and unsuccessful in being taken up by the industry. Participatory modelling, in which end-users become part of the design process, has improved the usability and uptake of prior models.

This review of the literature on MAS and related modelling techniques was undertaken to support the Rural Futures FRST research progamme. It hopefully provides some guidance on the essential components of a model, methods for modelling each component, and processes for assembling an appropriate and usable model. With a successful model, the programme should be able to assess the macro-level emergent properties of New Zealand agriculture by simulating micro-level behaviour of farms and farmers.

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